University of Tennessee, Knoxville

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Supervised Undergraduate Student Research and Creative Work

5-2021

The duality of fashion: How industry norms impact market returns in the fashion industry

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THE DUALITY OF FASHION:

How industry norms impact market returns in the fashion industry

by

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Department of Economics
Honors Undergraduate Thesis
University of Tennessee, Knoxville
April 2021

Designs produced in fashion industry exist at the helm of creative innovation and utilitarian construction. The dual-nature of the clothing we wear, to cover our bodies and to express our tastes, has important implications for regulating copying and counterfeiting in an industry that thrives through its unified effort toward trend-based seasonal output. Understanding how fashion firms interact with their available intellectual property (IP) protections (i.e., patents, copyrights, trademarks) and how they leverage these can be a useful tool to guide firm and industry-level decisions. I analyze sentiment variation across IP infringement news headlines in the fashion and consumer technology industries using text analysis techniques and find no significant variation across the entire sample, on average. Through the event study methodology, I observe abnormal returns in the stock market as investors react to news of IP infringement in both the fashion and consumer technology industries. A Z-test for significance determines that the average cumulative abnormal return did not indicate significant wealth effects in the days following the media headlines in either industry. I then perform an econometric study of the impact of news headline sentiment on cumulative abnormal returns to understand whether or not the market is receiving value messages fashion's norms-based regulatory system. I find that the sentiment effects on abnormal returns do not vary across industry, suggesting that media messaging in the fashion is not adequately compensating the lack of state-backed protections offered to its designers.

Keywords: Fashion; News; Event study; Sentiment analysis

This paper is accompanied by an interactive Jupyter Notebook found here:
https://github.com/zcarte12/zcarte/blob/main/Thesis%20Draft%20Four.ipynb

1. Introduction

Intellectual property (IP) refers to creations of the mind – commonly thought of as artistic works, inventions, technologies, and industrial designs. Such creations are not a new phenomenon, but the formalized definition and protection of IP on a global scale is a somewhat modern movement. Understanding how firms interact with their available IP protections (i.e., patents, copyrights, trademarks) and ultimately how they leverage these protections can be a useful tool to guide both firm and industry-level decisions. Since IP protections offer firms the ability to generate value through innovation without unjust competition, their effects are far-reaching in many industries. Creative and cultural industries (CCIs), in particular, have struggled to incorporate formalized regulations that meet the needs of both the artistic and economic aspects of the goods or services rendered. Many participants in CCIs believe the goal of intellectual property protection should be to uphold integrity and intrinsic value (Loangkote, 2011). However, at its core the regulation and protection of works stems from economic policy decisions dating back to the 15th century under Venetian Act of 1747.[1] According to Article I, Section 8, Clause 8, in the US Constitution, the goal of the modern U.S. patent system is to create leverage for innovators to gain capital and attract investors to thus encourage the advancement of science and technology (Graham & Vishnubhakat, 2013). High levels of formal protections have allowed companies to innovate and generate market power, but there is evidence that certain industries reap more benefits from strong IP regimes than others. A study produced by the Intellectual Property Office in the U.K. found that patents and their associated premiums, the revenue value generated from obtaining patents, have a significant and causal outcome on revenues in the biotech and pharma industries, as well as those in computer technologies and instruments to a lesser degree (Arora et al. 2012). Each of these industries falls within the manufacturing industry, but there are clearly some specializations that generate more returns from current protection offerings than others. This finding suggests that even within industry groups, there are inequities in the value of obtaining formal IP protections. Across industry lines, and especially for CCIs, the value derived from regulation will vary even more because of the lack of specificity in current IP laws (Raustiala & Sprigman, 2012).

The fashion industry is one such sector in the scheme of CCIs that has not seen the same level of protection held by its creative counterparts. Trademarking and copyrighting offer designers to protect their brand image and 2-dimensional aspects of a garment. Design patenting fails to protect clothing and footwear because of their dual utilitarian and aesthetic nature. Still, some argue that the fashion industry may stand to benefit from its lack of unique IP protections (Raustiala & Sprigman, 2006: Cass & Hylton, 2013). In the absence of a tailored IP law that incentivizes fashion innovation, a social norms system of regulation may have emerged (Noto La Diega, 2019). Understanding the effectiveness of these social norms poses an exciting challenge for studies exploring the firm and industry level efficiency of the fashion marker.

Tracking the financial and reputational repercussions of any firm-level decision poses a challenge that Dasgupta et al. (1998) offer might be answered in capital markets. Capital market reactions to the level of litigation pursued by firms should indicate investor sentiment about the value of pursuing legal action to protect IP in the fashion industry. Comparing this reaction to a control industry might reveal whether or not social norms influence investor decisions. Further, there may be evidence that the norms-based regulation is working efficiently if design piracy has significant and negative impacts on firm value.

[1] *See* Sichelman, T., & O'Connor, S. (2012). The Venetian Act of 1747 included provisions that protected individual inventors. Under the previous guild system, innovation was left solely to government appointed monopolies (i.e., artisan and merchant guild members). Serving as what many scholars identify as the basis for modern patent law, this 15th century system highlights a vital economic theory: increasing protection encourages investment in R&D which generates value for a firm.

In this paper, I assess whether or not the U.S. stock market reacts to media coverage of IP infringement cases in the fashion industry, comparing these results to similar announcements and reactions in consumer technology. I additionally analyze whether the role of news headlines and their associated sentiment varies between the fashion industry and the consumer technology industry.

The rest of the paper is set up as follows:

Section 2 offers analysis of the fashion industry and its current IP protections. Section 3 explores prior evidence of market reaction to IP infringement. In Section 4, I detail methods used to construct my dataset(s). Section 5 outlines the formal event study framework, and Section 6 develops the resulting null and alternative hypotheses. Results are detailed and discussed in Section 7. Lastly, a conclusion section offers suggestions for future applications and revisions while exploring the implications of my achieved results.

2. Industry Analysis

With a global revenue of over $1.3 trillion in 2012, the fashion industry surpasses the economic power of the software, motion picture, music, and books industries combined (Raustiala & Sprigman, 2012).

From 2017 to 2019, the United States saw an 18.5% increase in dollars spent on apparel and footwear, up to $403 billion from $340 billion (U.S. Congress Joint Economic Committee, 2019). Over the last decade, more than 952 apparel companies re-shored manufacturing, signaling increased interest in U.S.-based production capacities because of the growing demand for fast, trend-driven fashions (U.S. Congress Joint Economic Committee, 2019). This means more companies will be subject to the current regulation practices within the country's notoriously lax intellectual property regime for the fashion industry.

2.1 Positioning the Fashion Industry within the Current IP System

There are three main regimes that reside over intellectual property: trademark, copyright, and patent laws. Each provides innovators with specific set of protections, depending on the product or idea's characteristics. Trademark law protects branding, commonly seen in a brand's distinctive logos and graphics. Patent law protects product and process inventions. Copyright law protects the more abstract realms such as art, music, film, and literature. The particular obstacle faced by fashion innovators lies in the diversified role of clothing as both a symbolic cultural movement and a utilitarian function of society. The economic fate of the fashion industry then relies on its consumers' response to the clothing's dual nature, existing as both practical in purpose and yet often artistic in nature (Miller, 2014). These sometimes-opposing characteristics are what some scholars attribute to the relatively low levels of IP regulation and litigation within the global industry and especially within the United States (Raustiala & Sprigman, 2006; Miller, 2014).

Much attention has been given to The Lanham Act's ability to protect fashions. This Act established the trademarking regime within the United States and laid the foundation for fashion designers to receive protection for the visual nature of their works. Since trademark law places emphasis on the recognizability and strength of a brand, there is contention over whether or not trademarking and trade dress[2] are adequate protection for the aesthetically unique designs of creators not backed by large capital of established conglomerates like LVMH and Kering (Mills, 2009; Raustiala & Sprigman 2012; Harvard Law Review, 2014). The clothing industry accounts for 5.72% of all 2,187,967 active trademark registrations in the U.S. from 2004 until 2013 (U.S. Patent and Trademark Office, 2016). Jewelry and leather goods each add 1.12% and 1.32%, respectively. At 125,252 trademarks held from 2004 through

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[2] Here, *trade dress* refers to the visually distinct and brand-identifying aspects of an object. *See* Raustiala & Sprigman (2012) and Harvard Law Review (2014).

2013, clothing stores (NAICS 448) rank 5th in total trademark registrations across all industries (U.S. Patent and Trademark Office, 2016). The computer and scientific industry (NAICS 54), which ranks 4th in the same report, employed about 14% more U.S. citizens in 2019 according to the Bureau of Labor Statistics. This suggests that there is a high intensity of trademarking within the fashion industry. In 2013, there would have been 88 trademark registrations per 1,000 employees working in the retail clothing industry.[3] This suggests a reliance on brand-names to convey value to the market.

Trademarking protects the overall brand of a firm but does not necessarily incentivize innovation; rather, it incentivizes relevance. Extending this theory to the consumer technology space, Apple Inc.'s innovative success is not wholly because of the brand protection of their distinguishable logo or sleek aesthetics. The projection of the brand helps Apple reach its target market. However, without the ability to litigate against piracy of their actual products and the underlying technologies supporting these utilitarian goods, their market relevance would drop substantially as low-cost alternatives gain consumer attention. The consumer technology space, in particular, is notorious for its intense litigation practices surrounding IP infringement. Everything from internal software and hardware concepts to external aesthetics and design receives frequent protection year after year. Communications equipment accounted for 65,854 of the patents held from 2003 until 2019 (U.S. Patent and Trademark Office, 2016). Fashion designs, despite also requiring conceptual framework inputs and externally aesthetic outputs, have historically not received the same level of litigation or protection. The number of patents in the apparel industry from 2003 to 2013 was just 4,623 (U.S. Patent and Trademark Office, 2016), likely because design patents under current U.S. law do not extend to the functional aspects of articles produced (Mills, 2009). This inability to distinguish between utility and aesthetics also makes traditional copyright law an inviable option for the fashion industry.

Where rights do extend to independent artists and their purely aesthetic creations[4], copyright law fails to protect design elements that are deemed "useful" and therefore prevents fashion designers from protecting the whole of a particular design. In the. *Star Athletica, LLC* v. *Varsity Brands, Inc* case, a distinctive stripe on a cheerleading uniform was analyzed separate from the entire garment. The stripe was afforded further copyright protection, but the uniform as a whole still remains unprotected. *Star Athletica, LLC* v. *Varsity Brands, Inc* established greater inclusion of certain design elements of useful articles if such an element can be analyzed separately of the utilitarian functions, according to Harvard Law Review. Even still, the updates to copyright law do not adequately protect an entire physical design from being copied. Given that the industry still lacks comprehensive protections for a design in its entirety, creators remain vulnerable to design piracy and imitation. This vulnerability, while likely a driver of innovation for the industry as a whole, denies the original designers an artistic integrity experienced by creators in other aesthetic markets. The downfalls of the patent and copyright regimes explain why the fashion industry relies almost exclusively on trademarking for protection.

2.2 Contention within the Industry

Due to the lack of direct protections offered to fashion designs, some inter-industry contention over the type and amount of regulation that should be offered exists. Mays (2019) notes that design-heavy couture houses want strict protection for their work while brand-centered retailers of copied designs hope to hold onto the traditionally lax IP system.

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[3] Calculated by dividing the total number of trademark registrations from 2004-2013 (USPTO) by the December 2013 employment in the clothing industry (U.S. Department of Labor BLS).

[4] Independent artistry is considered a copyright-intensive industry, while the fashion industry (that notably relies on similar creative inputs) is considered trademark-intensive by the USPTO and WIPO.

The absence of tailored intellectual property protections for fashion designs led to a shift toward brand- or logo- centered protections through trademarking and thus discourages competition in the industry.[5] Economic theory supports this sentiment. Traditionally, efficient market outcomes only exist in a system with enforceable property rights (Hardin, 1968). Proponents of increased IP protections often call for the preservation of design integrity – a goal that trademarking cannot meet since the action only protects the recognizability of a garment and its artistic qualities (Harvard Law Review, 2014). The trend toward trademarking also explains why retailers – who are loyal to a plurality of brands, rather than in-house designs – might be interested in holding onto the lax protections (Mays, 2019). Under current law, it is perfectly likely that a large department store like the United States' Nordstrom could carry both the luxury Gucci horse bit loafers *and* their low-end knockoff by high-street designer Sam Edelman. Multi-brand retailers are better able to drive up their profits when they can reach two distinct sets of customers without facilitating infringement. If IP regimes were expanded to protect the whole of a fashion design and its utility, retailers might not enjoy the same market diversification.

2.3 Evidence and Ramifications of a Norms-Based IP Regime

A key difference between the fashion and consumer technology industries challenges the assumption that IP litigation holds long-term benefits for firms. The fashion industry likely operates under a norms-based system of IP regulation, wherein legal battles over infringement are rarely brought to the same scale as consumer technologies. The origins of this regulatory system in the fashion industry dates back to Fashion Originators Guild of America in 1930s where members were able to register their designs so as to facilitate industry-level regulation (Merges, 2004). When the whole of a community relies on the same resources to thrive, a "commons" emerges. In the fashion industry, this commons is what drives the cyclical structure: seasonal trends. The success of a fashion brand's collection relies on its ability to meet the trend-driven demand of its consumers. Yet the entire industry must set the trends, generating some unanimous elements that connect with current consumers. The result is a commons where trends are determined and administered by creators within the entire industry. The "information commons" or perhaps for the fashion industry, the "*trend* commons" emerging from norms-based IP regulation might perform efficiently with little need for regulation (Fauchard & Hippel, 2008). Fauchard and Hippel (2008) note that four characteristics must be present in order for a norms-based regulatory system to work:

> "(1) The protection of IP is important to a group of individuals or firms; (2) group members consider any extant law-based or other form of IP protection inadequate or unsatisfactory in some way; (3) group members control economic rewards and/or sanctions valued by group members; and (4) actions by nongroup members cannot destroy the value of sustaining the norm within the group or destroy the value of rewards and sanctions available to enforce the norm."

Fauchard and Hippel's third requirement is of particular interest to my study. In any market, the existence of a commons encourages free riding threatens inefficiencies (Hardin,1968). Creative industries like fashion design that rely on unified trend cycles are particularly at-risk here if piracy attempts are met wholly unchallenged even if they are not formally litigated. Noto La Diega (2019) empirically finds that a norms-based regulation of power and contract law across fashion brands seems to fill the gaps that current U.S. regulations leave. Other creative and cultural industries like the French haute culinary market have been shown to thrive under this quasi-regulatory system (Fauchard & Hippel, 2008). Given the similarities of the design- and process-related haute cuisine and haute couture, it makes sense that there might be an unspoken norms "enforcement" keeping design piracy from deteriorating the economic returns of rights-holders. If true, I hypothesize that some of this negative social sentiment toward infringement attempts should show up in articles reporting on piracy in the field of fashion.

2.4 Sentiment Analysis

Sentiment analysis and natural language processing (NLP) is a somewhat new and rapidly expanding field of research which aims to interpret the tone and polarity of bodies of text. Some research within the fashion industry has already identified links between emotionally charged consumer preferences revealed through Twitter discussions and trend emersion (Giri et al., 2018). Other work within the banking sector reveals that stock returns are significantly impacted by negative sentiment in media coverage (Carlini et al., 2020).

Negative sentiment in media coverage of the financial sector has previously been linked to short-term downward pressure on market returns. Importantly, most abnormal stock reactions to media coverage come from extremely negative news (Tetlock, 2007; Peress, 2008). If sentiment polarity in the fashion industry varies (i.e., is more or less negative than consumer technology), as hypothesized later in this paper, then its coverage on media sites might therefore influence the cumulative abnormal returns in the market and communicate the norms-enforced repercussions of infringement.

3. Evidence of Abnormal Market Reaction to IP Infringement Litigation Announcements

Modern scholars have been attempting to quantify the value of patenting for high-tech industries and its ability to create leverage. For example, Lerner (1994) suggests that broad patents with high sub-classes and citation counts generate more firm value. His study finds that, on average, when the average patent scope increases by one standard deviation, average firm value increased by 21%. Lerner (1994) also finds that broad patents are statistically more likely to be litigated. However, some argue that encouraging these broadened patents, which thereby lack specificity, causes consumer and producer inefficiencies during litigation cycles (Graham & Vishnubhakat, 2013). For example, in the notorious *Apple Inc. v. Samsung Electronics Co.*, foreign markets like Germany and Australia saw a significant delay in receiving Samsung's Galaxy products during the patent war between the two tech giants. Still, Graham & Vishnubhakat (2013) offer that the inefficiencies of IP litigation, which cause a short-term stall in access to consumers, are overshadowed by the long-term benefits of innovation. Such a perspective might explain why, despite the damages associated with litigation efforts, the high-tech patents of the consumer technology industry were litigated earnestly during the "Smartphone Wars" from 2009 through 2018. The same litigation patterns are not seen in the fashion industry, though. Given the fast-paced and cyclical nature of trends in the fashion industry, where many brands design 52 collections per year (Mays, 2019), these short-term inefficiencies from litigation may never be recovered in the long run. Firms in the fashion industry might miss key trend cycles and consumption opportunities altogether.

There exists a relatively rich body of literature examining market reactions to patent infringement cases. However, these studies often deal exclusively with firms falling within the technology industry. To my knowledge, fewer attempts have been made to analyze how the market reacts to infringement announcements within industries that are not as heavily regulated. Bhagat and Romano (2002) explain the origins of event studies as a way to test the efficiency of the market; however, they note that financial economists are now using this methodology to observe the "benefit of corporate and securities law" from the perspective of investor welfare. Lanjouw and Lerner (1998) suggest that event studies examining "the change in firm value upon the filing of litigation" might be the most promising method to link high levels of patent litigation to fluctuating market value. For example, Bhagat et al. (1994) predicted that after the initial filing of a suit, a defendant's stock declines by roughly 1%, while the plaintiff shows no significant change at first. Further, Bhagat et al. (1998) find that defendants involved in lawsuits with other firms lose 0.75% in the stock market, suggesting that patent litigation is a meaningful economic event in the eyes of stakeholders. These, along with a broader literature of litigation event studies, emphasize the impact of patent litigation announcements on firm value. However, as discussed above, the fashion industry rarely relies solely on patent claims and instead aims to protect brands through trademarking.

Fewer studies focus on market reactions to attacks on the brand. Ertekin et al (2018) observe that the short-term effect of trademark infringement shows up as a statistically significant negative event in the eyes of stakeholders. However, their event study finds that there are long-term benefits to pursuing aggressive legal action, even if the market responds negatively in the short-term. This echoes the findings from Graham and Vishnubhakat (2013) who suggest that inefficiencies and negative consumer spillover effects caused by litigation of patents will eventually be mitigated by the long term returns of an investment in litigation efforts. In deciding whether or not to litigate, brand managers must consider the market repercussions of introducing an element of brand fragility to consumers. To my knowledge, there are no current studies observing how the market reacts uniquely to infringement announcements within the fashion industry.

4. Constructing the Dataset

I build the dataset in four steps: (1) gathering relevant news articles which discuss IP infringement (2) analyzing the sentiment of these headlines and appending this to the data (3) generating a random sample of publicly traded firms appearing in the articles (4) scraping Yahoo! Finance for the daily returns of each firm and the market, the S&P 500.

4.1 Gathering News Articles. In the first step of this multi-part analysis, I obtain news articles from the Dow Jones Factiva news article database. Since I am interested in understanding how the variation in news sentiment and distribution affects equity values of firms within the fashion and technology industries, I perform two industry-based searches. I use the following parameters to narrow the search results in Factiva:

(1) Industry: Fashion[6] or Consumer Technology
(2) Region (United States)
(3) Contains at least one of these words: “dispute”, “sue(s)”, “infringement”
(4) Subject: Intellectual Property Rights
(5) Publish date: January 1, 2010, to January 1, 2020

Using the Factiva’s search download capabilities, I gather the resulting news articles into unique HTML files that contain identifying information such as publication date, source, and author, as well as the content of the article. Factiva limits its download capabilities such that users can download search results one page at a time. My search parameters yield eight pages of fashion articles and eleven pages of consumer technology articles. I concatenate the identification and content data contained in each HTML file into two data frames: one containing the fashion articles and one containing the consumer technology articles. I analyze sentiment variation across industries and create a set of litigation announcement dates using the data contained in the two data frames.

4.2 Sentiment Analysis. I use the lexicon and rule-based VADER (Valence Aware Dictionary and sEntiment Reasoner) open-source python tool developed by Hutto and Gilbert (2014) to analyze the sentiment of news headlines within my two data frames. VADER is specifically designed to handle sentence-level sentiment – with punctuation, capitalization, modifiers, and negations impacting the overall score. I choose VADER as my sentiment analysis tool for a few reasons. First, VADER was initially developed using Tweets and later expanded using 500 *New York Times* opinion articles, so it poses significant advantages for short-form texts like the news headlines analyzed in my study. Additionally, its simplicity and efficiency make it a convenient tool for investors who use sentiment analysis tools to conduct their stock market research. VADER assigns a sentiment observation (positive

[6] Note that “Fashion” is defined by the Designer Clothing, Clothing, Footwear, and Sports Clothing/Footwear categories on Dow Jones Factiva.

or negative) and determines the polarity of such a score, producing scores ranging from -4 to +4. I append these scores onto the appropriate article within the datasets for further evaluation.

4.3 Creating a Random Sample of Event Dates. Due to the nature of an event study methodology, I need access to firm-level daily returns. I therefore require that at least one firm mentioned in the article's headline is publicly traded in the United States, either in the New York Stock Exchange or the NASDAQ. A random subsample representing 10% of the fashion and consumer technology datasets is generated, resulting in 218 raw observations. From this, I narrow the sample set to 39 events. I repeat the data sampling method at 30% of the initial dataset. From this sample, I then append only the first 30 events from each of the two industry categories to my initial random dataset. When more than one publicly traded company is involved in the suit, the event observation is doubled to track market reactions for both plaintiff and defendant firms.

4.4 Scraping Yahoo! Finance. I pull adjusted daily stock returns from January 1, 2010, until December 31, 2019, for each company in the random sample using the Yahoo! Finance market data downloader. I also pull the most recently recorded total revenue, total number of employees, enterprise value, and regular daily stock trading volume for each firm. I use this financial data during the econometrics portion of the study described in Section 5.5.

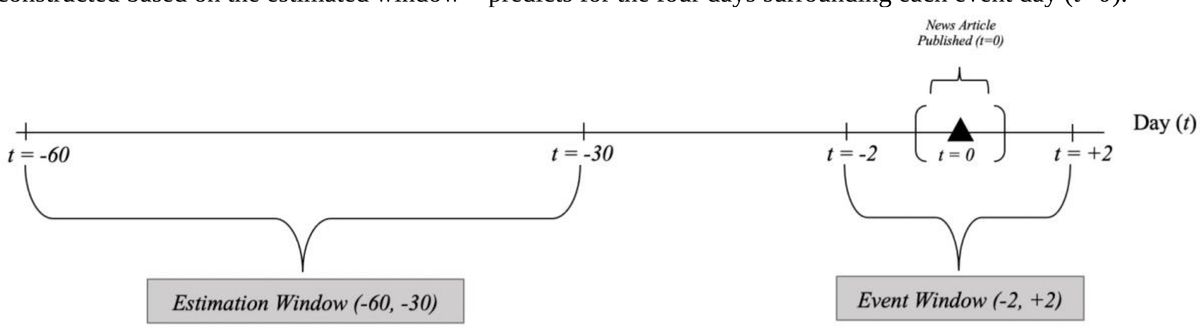
5. Event Study Framework

As detailed by MacKinlay (1997) there are four standard steps in performing an event study, outlined in the following section. For each firm, I identify the news article publishing date and a selected event and estimation window, obtain the actual daily firm and market earnings, and predict the expected returns of the firm based on past performance in the stock market and determine abnormalities. In the fourth step, I study short-term wealth effects by summing the daily abnormalities across an event window of five days.

5.1 Selecting the Event and Estimation Windows. I adopt a five-day event window from day -2 to day 2, where day 0 is each article's publishing date. The 30-day estimation window with which I develop my market model starts runs from day -60 until day -30. Thus, I base my predicted returns model on stock return data from roughly a month prior to the studied news article under the assumption that this window of time captures the normal performance of a security and the market.

Figure 1. Event Study Conceptual Framework

Figure 1 shows the theoretical breakdown of the event study methodology employed in this study. Note that the estimation window, which begins 60 days before the news article is published and lasts for 30 days, is used to estimate the normal performance of each firm in the stock market. To study the short-term effects of the media coverage, I adopt a five-day event window containing returns data from two days prior to the event in question until two days after. This event window is used to analyze the degree to which the actual returns of a firm vary from what the model – constructed based on the estimated window – predicts for the four days surrounding each event day (*t=0*).



5.2 Identifying Actual Stock Returns. I scrape Yahoo! Finance and generate a dataset containing the daily adjusted closing price for each firm and my market comparison, the S&P500.

5.3 Generating the Predicted Return Using the Market Model. According to MacKinlay (1997), the market model "relates the return of any given security to the return of the market portfolio" through OLS regression which predicts the firm's returns. For any firm *i* the market model is:

$$R_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} R_{\mathrm{mt}} + \varepsilon_{\mathrm{it}} \quad (1)$$

where R_{it} and R_{mt} are the period-*t* returns on the firm and market, respectively, and α_{i} and β_{i} are the firm-specific parameters from the estimation period. Note that to generate R_{it} and R_{mt} are expressed as the natural log of the security's price in current period *t* divided by period *t-1*'s price. This allows me to interpret returns, abnormal returns, and cumulative abnormal returns as percentage changes.

Computing the Abnormal Return. To retrieve the abnormal return (AR) for security *i* at period-*t*, I subtract the predicted return generated by the estimating model in Equation 1 from the actual return R_{it}:

$$AR_{it} = R_{\mathrm{it}} - \alpha_{\mathrm{i}} - \beta_{\mathrm{i}} R_{\mathrm{mt}} + \varepsilon_{\mathrm{it}} \quad (2)$$

5.4 Computing Cumulative Abnormal Returns. I then calculate the cumulative abnormal returns in the period from 2 days before to news article publication to 2 days prior:

$$CAR_{it} = \sum_{\mathrm{t}=-2}^{\mathrm{t}=2} AR_{it} \quad (3)$$

Because I am interested in understanding the impact of IP infringement news articles on the entire sample, I also compute average CARs (CAARs):

$$CAAR_{it} \frac{1}{\mathrm{N}} \sum_{\mathrm{t}=-2}^{\mathrm{t}=2} CAR_{it} \quad (4)$$

where the variance of $CAAR_{it}$ is:

$$var(CAAR_{it}) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2 (\mathrm{T}_1, \mathrm{T}_2) \quad (5)$$

Testing for significance. I test the statistical significance of the CAARs using a standard Z-test which divides the CAARs by the square-root of the zero conditional mean and conditional variance standard error (T_1):

$$Z = \frac{CAAR_{it}(T_1, T_2)}{\sqrt{\left(var(CAAR_{it})\right)^2}} \quad (6)$$

where a Z-statistic of ±1.96 indicates a significant event.

5.5 Econometric Model

Because of the differing nature of IP litigation cases and media coverage across the tech and creative industries, I want to track how variance in the sentiment surrounding infringement within these industries impacts stock returns. Previous studies have found that negative headlines cause statistically significant abnormal returns. For example, Carlini et al. (2020) analyze the impact of media coverage on banks' abnormal stock returns. In order to discern how much of the variation in the cumulative abnormal returns can be attributed to the sentiment of the headline, I adopt the following empirical model:

$$CAR_{it} = \beta_1 Sentiment_{it} + \beta_2 Fashion_i + \beta_3 Plaintiff_i + \beta_4 Size_i + \beta_5 Efficiency_i + \beta_6 Volume_i + \beta_6 Public_i\, \varepsilon_{it} + \beta_6 Interact_i + \beta_7 Industry\_FE_i + \varepsilon_{it} \quad (7)$$

where the coefficient on the variable of interest, $Sentiment_{it}$, implies how much the headline sentiment score for the article associated with firm *i* at time *t* impacted equity values in the market. I also control for industry by allowing a dummy variable, $Fashion_i$, to equal 1 if the firm is in the fashion industry and 0 if the firm is in the consumer technology space. I control for variation within the two categories (fashion and non-fashion) by including dummy variables for the primary industry classification assigned to the firm *i*, as determined by Yahoo! Finance The interaction term, $Interact_{it}$, can be interpreted as the difference in cumulative abnormal returns attributed to the sentiment of headline when comparing the fashion and non-fashion groups. The model also controls for variation in financial statements across each firm, but it reports the most recent statistics rather than those describing the firm at time *t*. I explore the implications of this choice in Section 8 of this paper. $Size_i$ is determined by the most recent enterprise value of the firm. $Efficiency_i$ is computed by dividing the most recent total revenue by the total number of employees. Lastly, $Volume_i$ is the average number of shares traded in one day for firm *i*, as reported by Yahoo! Finance. Table 2 summarizes these along with all other variables used throughout the study.

Table 2. Description of Variables

Variable Name	Description
R_{it}	The closing price of the security *i* at time *t*
R_{mt}	The closing price of the S&P 500 at time *t*
AR_{it}	Variation from the predicted returns based on the market model.
CAR_{it}	The cumulative abnormal return from 2 days before to 2 days prior to the news article publication.
$Sentiment_{it}$	The sentiment score [-1, 1] associated with the news article's headline
$Fashion_i$	A dummy variable for the fashion industry (1 if fashion; 0 if consumer tech)
$Interact_{it}$	$Sentiment_{it}$ x $Fashion_i$
$Size_i$	Enterprise value of firm *i**
$Efficiency_i$	Total revenue / total number of employees*
$Volume_i$	Regular trading volume of firm *i**
$Public_i$	A dummy variable indicating that both firms listed in news headline are publicly owned (1 if public plaintiff and defendant; 0 if otherwise)
$Industry\_FE_i$	A dummy variable indicating firm industry (1 if particular industry; 0 if otherwise). One dummy for each industry is considered.

*Data comes from most recent report available on Yahoo! Finance.

6. Hypothesis Development

I develop three hypotheses in order to perform an empirically examine the relationship between industry, news sentiment, and market reactions to IP infringement.

Hypothesis 1: Sentiment Analysis Variance
First, I seek to understand whether the events in my larger sample of all 2,200 articles vary significantly across industry. A difference in means test analyzes whether the average sentiment score, as captured by VADER, varies significantly across the fashion and consumer technology industries where the null and alternative hypotheses are:

> H_0: *The sentiment within IP infringement news article headlines does not vary across industry.*
> H_A: *The null hypothesis is false.*

Hypothesis 2: Event Study for Abnormalities in the Stock Market
The goal of an event study is to determine whether or not a particular event yields significant wealth effects on the firm during an event window. Prior research suggests that litigation wars have a net negative effect on both the plaintiff and defendant when legal costs are considered (Bhagat et al., 1994), yet some find significant positive returns for the plaintiff upon the initial announcement of litigation (Raghu et al., 2007). Thus, *Hypothesis 2* will observe whether or not firms experienced significant market abnormalities in the aggregate, either positive or negative:

> H_0: *The cumulative abnormal returns for firm i at time t will be zero.*
> H_A: *The null hypothesis is false.*

Hypothesis 3: Econometric Analysis
The third step of my analysis employs OLS regression to tease out the factors contributing to the CARs generated using Equation 3. Based on prior evidence of the impact of media sentiment on stock returns in other industries (Tetlock, 2007; Carlini et al., 2020), I adopt a third hypothesis which explores whether the impact of news headline sentiment on the firms' returns varies across fashion and non-fashion firms in my sample:

> H_0: *Media sentiment effects on CARs do not vary when comparing industries.*
> H_A: *The null hypothesis is false.*

7. Results and Discussion

7.1 H1 – Headline sentiment scores do not vary by industry

Table 3 reports the mean sentiment scores by year and industry. Even though VADER has the ability to assign scores from -4 to +4, the 2,200 articles included in my Factiva scrape would be considered only slightly negative on average. The mean sentiment score for fashion headlines was -0.064 while consumer technology articles had a slightly more pronounced mean score of -0.359.

Table 3. Mean Sentiment of Articles by Industry and Year – Hypothesis 1

Time and quantity data is pulled from Dow Jones' Factiva. Mean sentiment by year is derived using the sentiment scores assigned by VADER sentiment analysis tool. A difference in means test (labeled *t-stat*) reveals whether or not the mean sentiment in Panel A varies significantly from the mean sentiment in Panel B.

	Panel A: Fashion		***Panel B: Consumer Technology***		
Year	Number of Articles	Mean Sentiment	Number of Articles	Mean Sentiment	*t-stat*
2010	104	0.03	48	-0.138	*-2.790*
2011	58	-0.07	40	-0.033	*0.512*
2012	100	-0.024	120	-0.137	*-2.520*
2013	74	0.015	91	-0.049	*-0.989*
2014	79	-0.172	160	0.002	*3.531*
2015	72	-0.094	135	-0.148	*-0.990*
2016	77	-0.112	143	0.009	*2.224*
2017	139	-0.087	126	-0.142	*-1.145*
2018	117	-0.124	186	-0.026	*2.229*
2019	125	-0.023	206	-0.085	*-1.482*
Total	*945*	*-0.064*	*1255*	*-0.070*	*-0.359*

A difference in means test reveals no statistically significant variation in mean sentiment across the total sample of fashion and consumer technology news articles. Individual years do show some statistically significant variation in means across the fashion and consumer technology industries, though. Namely, years 2010, 2012, 2014, 2016, and 2018 show t-statistics that indicate significantly different average sentiment used in reporting IP infringement cases in the fashion industry, compared to the consumer technology space.

7.2 H2 - The cumulative abnormal returns for firm i at time t will be zero.

In order to test whether significant cumulative wealth effects appear in my sample set, I treat the CARs values in three groups: the overall sample, fashion firms, and non-fashion firms. I run series of Z-tests (T_1) to determine whether the average aggregated cumulative abnormal returns (CAARs) are significant. Table 4 reports these results and reveals that the overall sample does not experience significant wealth effects during the days following an IP infringement case reported in the news.

Table 4. Significance of Average CARs (CAARs) – *Hypothesis 2*

Table 4 displays the results of a Z-test for significance on the mean CARs (CAARs) for the overall sample as well as the fashion and non-fashion groups. The event window (-2,0) tracks abnormal returns from two days prior to the article's publication date until the day of publishing (*t=0*). The average cumulative abnormalities for one and two days prior to publishing are reported in the event windows (-2,1) and (-2,2), respectively.

	Panel A: Total Sample		**Panel B: Fashion**		**Panel C: Not Fashion**	
Event Window	Mean CAR	T_1	Mean CAR	T_1	Mean CAR	T_1
(-2,0)	-0.0041	0.9632	-0.0097	0.9371	0.0022 (0.1614)	0.9866
(-2,1)	0.0106	0.9632	0.0073	0.9371	0.0212	0.9866
(-2,2)	-0.39	0.9632	-1.33	0.9371	0.1	0.9866
Observations	124		58		66	

Due to the lack of statistical significance, as determined by the Z-tests (T_1), I fail to reject the null *Hypothesis 2* that cumulative abnormal returns are zero. Neither the fashion nor the non-fashion group of firms experienced cumulative abnormal returns on average. This does not mean that firms were not significantly impacted by particular events, but it signals that on the whole, a singular IP infringement news headline does not significantly show up in the wealth effects for firms, regardless of industry. All of the sampled articles were housed on public websites, so the information was available to the market. While not considered in my study, formal press releases issued by the firms or financial newswires targeted at investors have been shown to impact CARs significantly (Carlini et al., 2020; Lagasio & Brogi, 2021). I would not expect articles published to mainstream or niche media websites to have the same impact as these alternative media types that have higher levels of exposure to investors. My insignificant result is not entirely surprising then when the media impact of each article is considered.

7.3 H3 – Media sentiment effects on CARs do not vary when comparing industries

I next perform an econometric analysis on the CARs resulting from Equation 3. I employ OLS regression to study the determinants of short-term investor reaction to IP infringement cases appearing in the news. To identify and test the media sentiment effects on CARs when comparing the two industries, I generate an interaction term between *Sentiment* and *Fashion* and include firm structure and news article controls. I then consider the significance and precision of my estimates. A breakdown of the average CARs experienced by the overall sample, as well as the fashion and non-fashion subsamples, appears in Table 5. I also report the average VADER sentiment scores for each group.

Table 5. Descriptive Statistics for Events in the Subsample

I provide the mean values of the independent variable, *CARs*, and the dependent variable *Sentiment* in Table 5. *CARs* are the calculated cumulative abnormal returns on the day of the article's publishing (*t=0*). *Sentiment* is a score from -4 to +4 and is calculated using the VADER lexicon described in Section 4. Standard deviations are reported in paratheses.

Variable	Overall Sample	Fashion	Not Fashion
CARs	-0.004	-0.010	0.002
	(0.118)	(0.059)	(0.161)
Sentiment	-0.135	-0.146	-0.123
	(0.321)	(.284)	(0.362)
Observations	124	58	66

Firm Structure Controls.

Previous studies in investor reaction to IP litigation identify the significance of firm market share on abnormal returns (Bhagat and Umesh 1997; Eterkin et al. 2018). I therefore control for variations in enterprise value through the variable $Size_i$. The variable $Efficiency_i$ controls for variations in total revenue per employee. Lastly, in order to measure and control for each firms' typical trading patterns in the stock market, I include $Volume_i$ which represents the regular daily trading volume, otherwise understood as the number of times stocks of a particular firm trade hands during any given day. The financial information used to control for firm structure is summarized in Table 6.

Table 6. Descriptive Financial Statistics for Companies Involved in Event Study

Mean values of the financial controls used in the OLS regression are described in Table 6. Data comes from Yahoo! Finance. Total Revenue and Enterprise Value (an expression of total market value) are expressed in USD. Regular Daily Trading Volume is the number of stocks that change hand in any given day for the firm *i*. Standard deviations are reported in parentheses.

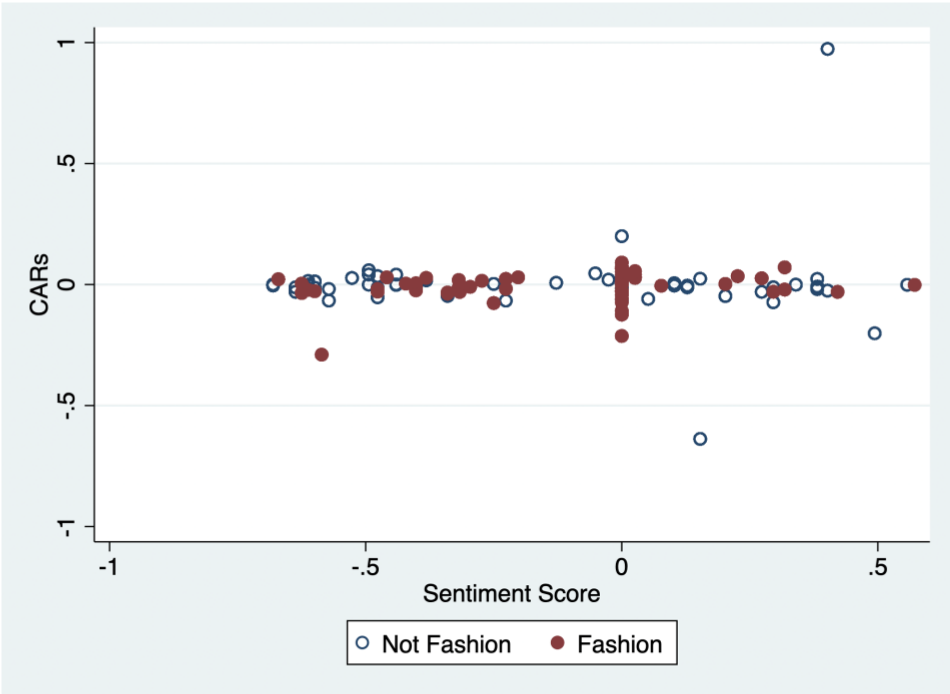
Variable	All Companies	Fashion	Not Fashion
Total Revenue	2.69E+10 (5.90E+10)	8.75E+09 (1.28E+10)	4.61E+10 (8.04E+10)
Enterprise Value	2.59E+11 (5.35E+11)	5.07E+10 (1.01E+11)	4.80E+10 (7.05E+11)
Total Number of Employees	56658.6 (80538.5)	30029.33 (38889.19)	84854.29 (102637.1)
Regular Daily Trading Volume	6141251 (1.32E+07)	1829101 (3123597)	1.07E+07 (1.78E+07)
Observations	35	18	17

News Article Controls.

In addition to controlling for the financial characteristics, I include an evaluation of the sentiment of each article's headline. This value is determined by VADER, which ranks short bodies of text by sentiment and polarity to yield a score ranging from -4 to +4. My particular subsample of 124 events has sentiment scores ranging from -0.6808 to 0.579, though much of the data is centered around the neutrality condition at 0, as displayed in the scatter plot below (Figure 2). I consider controlling for the fixed effects of particular publication dates and media outlets; however, these additions do not have much impact on the ability of the empirical model (Equation 6) to explain variation in the CARs in my sample and are therefore excluded.

Figure 2. Scatter Plot of Sentiment vs. CARs by Industry

Figure two plots the range of VADER-assigned sentiment scores associated with events in the fashion and non-fashion groups against the CARs calculated by Equation 3. The concentration of events centered around a sentiment score of 0 indicates that there are many headlines assigned a neutrality condition by VADER.



Industry Fixed Effects.
In addition to controlling for whether or not a firm is classified as a fashion company, I consider the fixed effects of unique industry classifications within the field of consumer technology. These fixed effects show up in Model 8 of the regressions described in Table 7.

7.4 Results of Regression Analysis

Table 7 displays the eight OLS regressions considered to analyze the impacts of news and firm characteristics on the observed cumulative abnormal returns. The only two characteristics found to be statistically significant are the efficiency of the firm, defined as total revenue divided by total number of employees, and whether or not both the plaintiff and the defendant in the case are publicly owned.

Financial Controls.
The impact of *Efficiency* on CARs, though significant at the 1% level, is quite small. Because CARs represent the percentage change in the cumulative effects of a firm's abnormal performance, a one unit increase in the revenue per employee results in a drop below the predicted returns by -4.75e-06%, all else equal. This result indicates that firm workforce structure may influence abnormal returns. Generating more revenue per employee comments on the ability of the firm to generate sales with minimal inputs. If this number increases, it either means that the firm is pulling in more revenue with the same number of employees or that the firm is generating the same amount of revenue but has lost employees. In either case, this would indicate that the value generated per employee has increased. Thus, if news of an IP infringement case were to reach the market, the mention of a company that generates more value per employee generates a small but significant negative return in the stock market. This signals that investors may view the threat of IP litigation as an attack on the efficiency of a firm.

The coefficient on *Public*, which identifies whether or not both firms involved in the IP infringement headline are publicly owned, is significant at the 5% level. All else equal, a public company involved in an IP infringement case with another public company, would expect to see a positive variation from normal returns by 5.1% ($p<0.05$). It makes intuitive sense that a case involving two firms whose stocks are traded in the capital market yields abnormal returns, since investors are essentially twice as likely to absorb the news about cross-firm litigation.

The enterprise value, a measure of firm size, was found to be insignificant ($p=0.471$) This result is somewhat surprising given prior research suggesting its importance (Bhagat and Umesh 1997; Eterkin et al. 2018). Given its importance in previous research, I keep this variable in my model as an imperfect control on market share. The volume of daily share trading is also found to be an insignificant determinant of abnormal returns in my dataset ($p= 0.845$). Because this is a measure that controls for the level of attention a firm receives in the stock market daily, I also keep this variable as a control in my model.

Table 7. Econometrics Results on CARS (-2,2) – *Hypothesis 3*

Results of the eight OLS regressions are described in this table. Industry fixed effects (*Industry_FE*) are included in Model 8 only. The variable of interest for *Hypothesis 3* is Interact and is included in Models 7 and 8. This variable is the interactive effects between headline sentiment (*Sentiment*) and whether or not the firm in in the fashion industry (*Fashion*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sentiment	0.0303	0.0297	0.0297	0.0296	0.0439	0.0531	0.0564	0.0551
	(0.91)	(0.89)	(0.89)	(0.88)	(1.51)	(1.84)	(1.48)	(1.40)
Fashion		-0.0112	-0.0112	-0.0114	-0.0292	-0.0159	-0.0170	0.0119
		(-0.53)	(-0.52)	(-0.42)	(-1.24)	(-0.66)	(-0.66)	(0.21)
Plaintiff			-0.00012	-0.00013	0.00931	0.0310	0.0310	0.0295
			(-0.01)	(-0.01)	(0.46)	(1.37)	(1.36)	(1.26)
Size				-2.10e-16	1.97e-14	1.11e-14	1.08e-14	2.40e-14
				(-0.01)	(1.37)	(0.45)	(0.44)	(0.72)
Efficiency					-4.75e-08***	-5.01e-08***	-5.01e-08***	-5.00e-08***
					(-6.49)	(-6.89)	(-6.85)	(-6.71)
Volume						6.40e-10	6.53e-10	2.02e-10
						(0.89)	(0.90)	(0.20)
Public						0.0497*	0.0497*	0.0510*
						(2.31)	(2.30)	(2.26)
Interact							-0.00779	-0.00528
							(-0.13)	(-0.09)
Industry_FE	NO	NO	NO	NO	NO	NO	NO	YES
Constant	-0.000039	0.00586	0.00594	0.00617	0.0382	-0.0106	-0.0102	-0.0379
	(0.00)	(0.36)	(0.26)	(0.21)	(1.51)	(-0.31)	(-0.30)	(-0.64)
Observations	124	124	124	124	124	124	124	124
R^2	0.0068	0.0091	0.0091	0.0091	0.2697	0.3066	0.3067	0.3103
Adjusted R^2	-0.0013	-0.0073	-0.0157	-0.0242	0.2387	0.2648	0.2585	0.2357

t statistics in parentheses
* p<0.05, **p<0.01, ***p<0.001

Industry and Sentiment Effects on CARs. Model 8 from Table 7 reveals the statistical insignificance of the regression coefficients on *Fashion* ($p=0.785$), *Sentiment* ($p=0.184$), and the interaction of these two terms, *Interact* ($p<0.840$). To understand the precision of these results, I begin by estimating whether or not the impact of a firm being in the fashion industry has precisely zero impact on abnormal returns in reaction to IP infringement cases. Table 8 describes the mean values of *Fashion* and *Sentiment,* as well as the standard deviations used to estimate the precision of the coefficients' insignificance.

Table 8. Describing the Means and Standard Deviations of *Fashion* and *Sentiment*

I use the means (μ) and standard deviations (σ) of *Fashion* and *Sentiment* described in this table in order to probe the true impact of the regression coefficients on the CARs in my sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Fashion	124	.532	.501	0	1
Sentiment	124	-.135	.322	-.681	.572

A probe of the coefficient β_2 reveals that the true impact of *Fashion* on CARs is contained within two standard deviations above ($\sigma=0.501$, $p<0.000$) and below ($\sigma= -0.501$, $p<0.000$) a value of 0 for β_2. A similar probe of β_3 finds that the true impact of *Sentiment* will fall between two standard deviations above ($\sigma=0.322$, $p<0.000$) and below ($\sigma= - 0.322$, $p<0.000$). These results indicate that I can be confident that even if CARs have been influenced by the headline sentiment score or its industry classification as fashion or non-fashion, the precise impact will be quite small and very close to zero.

Table 9. Regression with Sentiment Centered Around the Mean

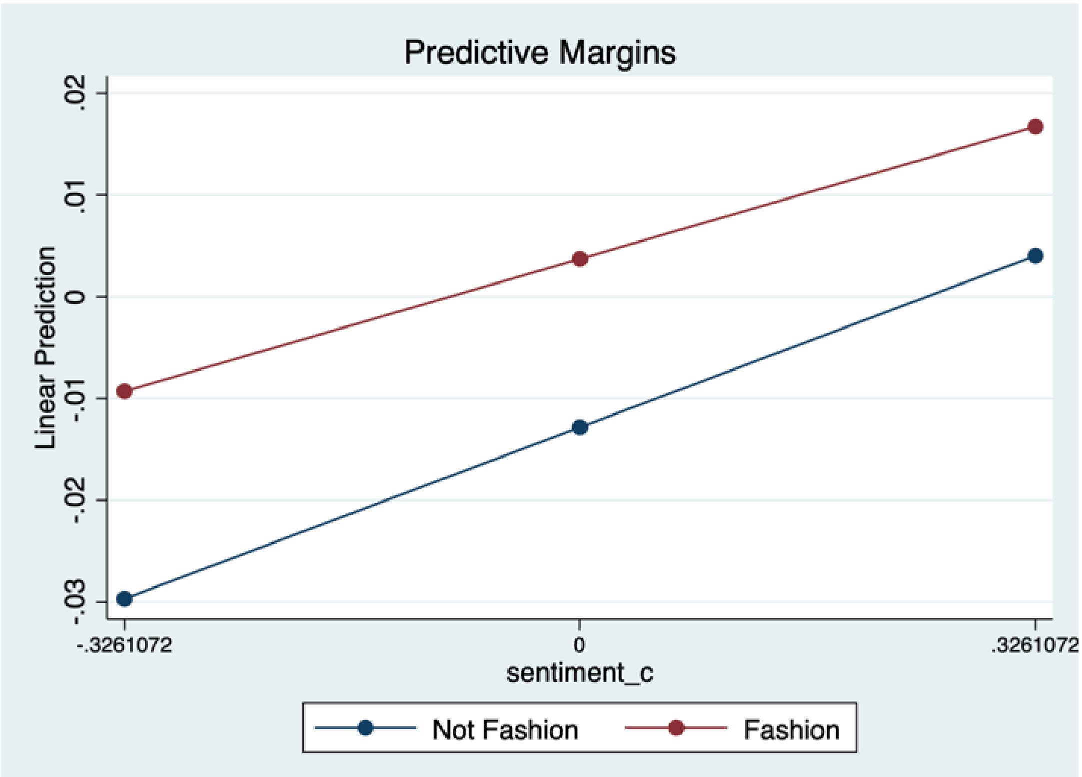
I repeat my OLS regression analysis using the parameters from Model 8 in Table 7 but center the *Sentiment* and *Interact* variables around their means and generates *Sentiment_c* and *Interact_c*.

	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Plaintiff	0.0295	0.0234	1.26	0.211	-0.0169	0.0760
Size	2.40E-14	3.31E-14	0.72	0.471	-4.16E-14	8.95E-14
Efficiency	-5.00E-08	7.46E-09	-6.71	0.000	-6.48E-08	-3.53E-08
Volume	2.02E-10	1.03E-09	0.2	0.845	-1.83E-09	2.24E-09
Public	0.0510206	0.0225515	2.26	0.026	0.0063333	0.0957079
Industry_FE	-	-	-	-	-	-
Fashion	-0.02128	0.02604	-0.82	0.416	-0.0729	0.03032
Sentiment_c	0.05171	0.03871	1.34	0.184	-0.0250	0.12842
Interact_c	-0.01181	0.05846	-0.2	0.840	-0.1276	0.10402
Constant	-0.04106	0.0251	-1.64	0.105	-0.0908	0.00868

Cross-Industry Variation in News Sentiment Effects on CARs. To test the null hypothesis that media sentiment effects on CARs do not vary across industries (*H3*), I examine whether the coefficient on the interaction of fashion and sentiment is statistically significant. I begin by creating a new variable called $Sentiment\_c_{it}$ which centers each sentiment score around the mean value shown in Table 8 ($\mu= 0.532$). I re-run the regression using this centered sentiment score in my specifications. The other control variables outside of the interaction term and its two components remain the same. The only significant predictors are still *Efficiency* ($p<0.000$) and *Public* ($p<0.05$). The interpretation of the interacted predictors changes, though. The regression result on *Sentiment_c* is the predicted relationship between CARs and the sentiment of headlines associated with firms not in the fashion industry. This means that the slope coefficient on *Fashion* is the difference in means on the fashion and non-fashion groups for media headlines scoring at the mean (μ= -0.135) on the centered sentiment variable. I interpret the difference in the mean sentiment score of a fashion article to be lower than a consumer technology article by about 2.13%. This would suggest that the total effect of being a fashion firm shows up as -3.31% ((β_2 = -0.0213) + (β_6 = -0.0118)) added to cumulative abnormal returns if all else is held equal. However, the coefficients on *Fashion*, *Sentiment_c*, and the interaction of these two are all still insignificant (p=0.416; p=0.184; p=0.84). This insignificance suggests that I cannot reject the null *Hypothesis 3* that media sentiment effects on CARs do not vary across industries. I further probe the interaction effects by obtaining the predictive margins, displayed in Figure 2.

Figure 2. Predictive Margins Plotted

Figure 2 plots the predictive margins of the centered sentiment score (*Sentiment_c*) for the fashion and non-fashion groups. The red line indicates that a firm is in the fashion industry while the blue line indicates otherwise. Note that the linear relationship is determined by the slope of the line that relates *Sentiment_c* and CARs.



Comparing the fashion and non-fashion groups, there is very little if any variation in the relationship between sentiment scores and the CARs for each event. The precise impact of *Interact* is likely to be zero, as shown by the probes in Table 10. The results of performing Wald tests for simple linear relationships show that the true impact of *Interact* on CARs is extremely likely to be contained within one standard deviation of zero above and below (p<0.000).

Table 10. Wald Tests on Regression Coefficient of Centered Interaction Variable (*Interact_c*)
This table summarizes the results of Walt tests of simple linear hypotheses that the coefficient on the centered *Interact_c* (β_6) is up to 2 standard deviations above and below zero.

	Value of Interact Tested	Prob > F	Conclusion
2 Std. Dev. Above	0.4449412	0.0000	Reject H_0 that β_6 is 2σ above 0.
1 Std. Dev. Above	0.2224706	0.0001	Reject H_0 that β_6 is 1σ above 0.
0.5 St. Dev. Above	.1112353	0.0548	Reject H_0 that β_6 is $.5\sigma$ above 0.*
Industry = 0	0	0.8402	Fail to reject H_0 that β_6 is 0.
0.5 St. Dev Below	-.1112353	0.0803	Reject H_0 that β_6 is $.5\sigma$ below 0.*
1 Std. Dev. Below	-0.2224706	0.0005	Reject H_0 that β_6 is 1σ below 0.
2 Std. Dev. Below	-0.4449412	0.0000	Reject H_0 that β_6 is 2σ below 0.

* Note: These are significant at the 10% level significance levels at 1%. A cautious researcher might fail to reject that the true value of the coefficient on the interaction between fashion and sentiment lies within 0.5 standard deviations above and below zero.

When the value of the coefficient on the centered interaction term comes within one-half standard deviations above and below the centered mean, statistical confidence drops to 90%. Given the statistically insignificant impacts of both *Fashion* and *Sentiment* on CARs, I am willing to accept, with 90% confidence, that the precisely estimated regression coefficient on *Interact* is contained within 0.5 standard deviations above and below zero.

8. Conclusions

While design piracy and counterfeiting are not unique phenomena to the fashion industry, the industry's trend commons and cyclical nature have encouraged lenience in state-backed litigation patterns. Instead, a norms-based system is thought to manage profit erosions from copying and counterfeiting (Merges, 2004; Fauchart & von Hippel, 2008; Noto La Diega, 2019). Whether or not the fashion industry is efficiently regulated by this norms-based system seems suspect, given the results of my study.

I find that average sentiment scores associated with IP infringement news headlines do not vary significantly across the fashion and consumer technology industries. To understand the relevance of moderate to low-traffic media headlines to investor decisions, I study the cumulative abnormal returns (CARs) of fashion and consumer technology firms in the five days surrounding IP infringement announcements in the news. On average, investors reacted negatively to IP infringement in the fashion industry (-1.0%) and positively to similar announcements in the consumer technology space (0.2%), though these reactions were not found to be statistically significant on the whole. Still, 63 out of the 124 events showed significant cumulative abnormal reactions during the five-day event window (see Appendix A). I perform regression analysis and find that the impact of headline sentiment variation across industries, represented by an interaction term between *Sentiment* and *Fashion*, is statistically insignificant and is likely contained within one standard deviation above and below zero ($p<0.000$).

Implications. The precisely estimated zero impact of the interaction term between *Sentiment* and *Fashion* may suggest that the market is not absorbing information from the socially regulated sentiment contained in news headlines. Without enabling investors to react appropriately to IP infringement cases, inefficient outcomes in the market may arise and profits may erode. The findings of my study question the idea that the fashion industry thrives in the absence of unique, state-backed protections. I find no evidence of significant variation in the sentiment attached to cases involving disputes between tech firms and those involving fashion firms. Yet technology infringement cases are surely litigated at a rate much higher than the fashion industry. Most fashion infringement cases are never litigated because of the rapid cycling through of styles that outpace the litigation cycles (Harvard Law Review, 2014). Other sources may communicate value messages in the capital market. Online forums and social media may serve as a regulating device where investors can determine whether or not to make trades of fashion securities. Press releases or financial newswires may also sufficiently communicate messages about brand and product strength to the market. Without norms-based regulation effects spilling into capital markets, it is difficult to say whether the current laissez faire approach to IP regulation is helping or hurting the fashion industry reach its innovative potential.

Future Work. My ability to estimate firm characteristics' impacts on abnormal returns is limited by a few important considerations. Future research might seek to advance the methods contained within this study. First, VADER, while an efficient tool for capturing the sentence-level sentiment of short bodies of text, is not pre-trained with all necessary keywords needed to analyze headlines concerning financial markets and intellectual property infringement. Previous attempts by larger research groups have attempted to incorporate lexicons Loughran and McDonald (2016) to some success (Shapiro et al., 2017). Future work should seek to incorporate appropriate lexicons into the sentiment analysis tool. Data availability constraints also impact my ability to accurately examine the effects of IP infringement across privately held firms, particularly in the fashion industry where much of the revenue is generated by privately held and/or family-owned businesses (McKinsey, 2020). Researchers should be aware, then, that the results of my study are not indicative of the entire industry's wealth effects resulting from IP infringement. I do not obtain multiple years of financial data for each firm in the subsample. An ideal study would control for the financial characteristics of the firm during the year of litigation, rather than for the most recently reported.

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Appendix A.

Companies and Dates Included in the Event Study. Note that a Z-stat of ±1.96 indicates that the firm experienced significant abnormal returns.

Ticker	Company Name	Event Date	Z-stat
AAPL	Apple Inc	15-Sep-11	0.84
		15-Jun-12	-0.94
		15-Aug-12	2.78
		16-Aug-12	3.50
		1-Nov-12	-4.36
		12-Dec-13	-5.63
		1-Apr-14	-0.45
		27-Aug-14	-0.06
		23-Mar-16	-0.18
		1-Aug-16	2.18
		11-Oct-16	4.51
		14-Dec-16	2.82
		6-Jul-17	-0.92
		24-Oct-17	-0.33
		29-Jan-18	-2.53
		18-Mar-19	4.81
		29-Mar-19	1.29
		8-Apr-19	2.81
ADDDF	Adidas	25-Nov-11	-3.13
		17-May-12	-0.93
		14-Apr-15	-17.57
		16-Feb-16	2.77
		23-Mar-16	0.44
		17-Mar-17	1.37
		15-Jun-17	0.09
		18-Jul-17	0.62
		2-Mar-18	-0.51
		13-Jun-18	-1.83
		8-Aug-18	1.72
		4-Sep-18	-1.29
		23-Sep-19	0.34
BB	Blackberry	6-Sep-18	-0.62
		27-Feb-19	4.62
BBRYF	Burberry	3-Dec-12	5.73
		9-Feb-16	-1.17
		27-Jul-16	2.47

		11-May-18	-2.98
COLM	Columbia Sportwear	6-Jul-11	-8.40
		2-May-14	0.67
		15-Aug-16	2.60
		31-Jan-19	4.68
CROX	Crocs	24-Feb-10	-2.51
		4-Jan-16	2.03
		11-Sep-18	1.98
CSCO	Cisco	17-Dec-19	4.40
DECK	Deckers Inc	24-Nov-17	-2.17
		26-Aug-19	0.11
FB	Facebook	6-Sep-18	-4.57
GES	Gucci	14-Feb-12	1.19
		29-Mar-12	-3.26
		9-Feb-15	-4.00
GOOG	LVMH	24-Mar-10	1.00
		6-Oct-10	-0.01
		15-Jun-12	1.37
		1-Nov-12	-0.53
		18-Apr-16	-0.04
		27-Mar-18	-1.56
		29-Apr-19	-1.92
		19-Nov-19	-1.69
JNJ	Janssen (Johnson & Johnson)	22-May-17	-6.59
LB	L Brands	8-Jan-18	-3.73
LLNW	Limelight Networks	10-Jan-14	-1.87
		13-Aug-15	-2.27
LVMUY	LVMH	24-Mar-10	-2.91
LVMUY		14-Apr-15	-1.90
LVMUY		20-Jun-17	-0.67
LVMUY		16-Jan-18	-0.39
LVMUY		11-Mar-19	0.27
MMM	3M	31-Dec-15	-2.61
MSFT	Microsoft	20-Nov-13	0.31
		19-Dec-14	0.84
		31-Dec-14	0.29
MSI	Motorola Solutions	13-Aug-18	0.03
NKE	Skechers	27-Jun-16	1.77

		8-Jul-16	5.16
		7-May-18	-2.31
		26-Jul-19	0.94
		1-Oct-19	4.36
NVDA	Nvidia	2-May-16	-5.68
ORCL	Oracle Corporation	6-Oct-10	2.13
		1-Nov-12	2.50
		27-Mar-18	-1.91
		29-Apr-19	-2.00
		19-Nov-19	-1.42
PMMAF	Puma	5-Jan-18	-37.48
		7-May-18	-37.20
		14-Feb-12	-1.45
		29-Mar-12	-1.61
		9-Feb-15	6.55
PRKR	ParkerVision Inc.	17-Oct-13	5.93
		18-Jun-18	-5.99
		22-Apr-19	-0.22
PVH	PVH Corp.	28-Nov-12	1.01
QCOM	Qualcomm Inc.	17-Oct-13	-2.31
		6-Jul-17	0.02
		29-Jan-18	-0.99
		18-Jun-18	1.71
		18-Jan-19	-3.48
		18-Mar-19	8.44
		29-Mar-19	1.76
		22-Apr-19	4.30
RL	Ralph Lauren	13-Feb-13	-0.24
		15-May-15	-1.77
SHLDQ	Sears Holdings	22-Mar-11	-2.48
SHOO	Steve Madden	8-Jul-15	2.96
SKX	Skechers	22-Mar-11	-1.58
SKX		19-Jun-14	-2.65
SKX		23-Jun-14	-1.22
SKX		10-Jul-14	-1.82
SKX		17-Sep-14	-2.62
SKX		8-Jul-15	-3.10
SKX		16-Feb-16	2.47
SKX		27-Jun-16	1.91

SKX		8-Jul-16	4.35
SKX		15-Jun-17	0.40
SKX		13-Jun-18	8.34
SKX		1-Oct-19	4.07
TGT	Target	11-May-18	3.09
TPR	Coach	23-Jul-12	1.31
TWTR	Twitter	27-Feb-19	-2.71
UAA	Under Armour	20-Aug-15	-4.61
		8-Aug-16	-0.13
		2-Nov-17	-2.42
VHC	VirnetX	1-Aug-16	-2.48